Amendments to the Specification

Please replace paragraph **[0023]** with the following rewritten paragraph:

[0023] Multiagent systems can be used in distributed problem solving. Multiagent systems can also be applied to problems involved in acting in the physical world, such as distributed traffic control, flexible manufacturing, the design of robotic systems, and self-assembly of structures. An exemplary embodiment of the systems and methods of this invention involves using multiagent systems to control smart matter. In particular, in such multiagent systems, there is a very tight coupling between the autonomous agents and their embedding in a physical space. In addition to informational interactions between agents when exchanging information, there are mechanical interactions between agents, whereby strength of these mechanical interactions decreases with the physical distance between the interacting agents. For ~~example. Consider~~example, consider the case where a beam buckling due to a heavy load is controlled by an array of smart piezoelectric actuators which sense the state of the straightness of the beam and piezoelectric actuators that operate to prevent buckling. The action of one piezoelectric actuator imparts displacement and stresses to a local region of the beam. These stresses and strains are then transmitted to other actuators/sensors in neighboring regions through the physics of rigid media.

Please replace paragraph **[0031]** with the following rewritten paragraph:

[0031] Fig. 1 is a flowchart outlining one exemplary method for making market-based model selection. As shown in Fig. 1, beginning in step S1100, control continues to step S1200, where each of N different system performance control models is assigned a weight w_i such that the sum of w_i from $i = 1$ to N equals 1. As step S1200 is repeated, a weight w_i may be reassigned as discussed herein. Next, in step S1300, for the next interval, a certain fraction a of each weight w_i, is "invested" or wagered. That is, for the i^{th} ~~model that if~~model, the i^{th} model's weight becomes aw_i, where $0 < a < 1$. This fraction may be the same for each model or may

depend on the weight itself. In various exemplary embodiments, models with large weights may be required to make larger investments, i.e., use larger values for a. Operation then continues to step S1400.

Please replace paragraph **[0034]** with the following rewritten paragraph:

[0034] In step S1800, the results of the prediction of each model are ranked. Next, in step S 1900, the invested amount, $\sum_{i=1}^{N} aw_i$, obtained from all N of the models, is split between the N models according to how well each model predicted the behavior of the system. For example, if the prediction error in the i^th^ model is e_i~~(t+Δ)~~(t+Δt) ~~= x(t+Δ) x_1(t), u(t)~~ x(t+Δt)-x_i (t+Δt; x(t), u(t)), then the fraction of the amount $\sum_{i=1}^{N} aw_i$ going to the i^th^ model is

$$\Delta w_i = a\left[\frac{1/\left(e_i^{\,2}+\sigma^2\right)}{\sum_{j=1}^{N} 1/\left(e_j^{\,2}+\sigma^2\right)}\right]$$

where σ^2 is an estimate of the noise variance. That is, there should be an incentive to predict better than the noise. In this case, the new model weights would be given by the difference between the amount invested and the return on investment. In other words:

$$w_i^{new} = (1-a)\, w_i^{old} + a\left[\frac{1/\left(e_i^{\,2}+\sigma^2\right)}{\sum_{j=1}^{N} 1/\left(e_j^{\,2}+\sigma^2\right)}\right]$$

This preserves the fact that the weights sum to 1.

Please replace paragraph **[0035]** with the following rewritten paragraph:

[0035] At any given time, the state of the system ~~is may~~ may be predicted, for example, jointly by:

$$\cancel{\hat{x}(t+\Delta t) = \sum_{i=1}^{N} w_i \hat{x}_i(t+\Delta t; \bar{x}(t), \bar{u}(t))}$$

$$x(t+\Delta t) = \sum_{i=1}^{N} w_i x_i(t+\Delta t; x(t), u(t))$$

Moreover, each model may also have a number of adjustable parameters that can be revised to maximize the accuracy of the models' predictions. As a given model adjusts its investment strategy by varying one or more of the adjustable parameters, that model will be rewarded. Operation then continues to step S2000.

Please replace paragraph **[0038]** with the following rewritten paragraph:

[0038] A second illustrative example involves expanding the definition of error to not only predict the next time step but the next *m* steps. The model that predicts a weighted integral of the squared error would be weighted more heavily ~~that one~~than one that does less well. Such an approach would be roughly analogous to a linear quadratic observer.

Please replace paragraph **[0039]** with the following rewritten paragraph:

[0039] Other embodiments entail changes in the way various models are re-weighted for successful prediction. The most extreme would be to assign all prediction to the one that does the best and none to the others. This approach would yield a prediction that was better than a less aggressive re-weight strategy but have the disadvantage of discontinuous changes in ~~predict~~ prediction leading to possible limit cycles and chattering in control.

Please replace paragraph **[0041]** with the following rewritten paragraph:

[0041] Market based model selection for control is almost identical to prediction except that a combined control is generated by

$$\cancel{\overline{U}(t) = \sum_{i=1}^{N} w_i \overline{U}(t)}$$

$$u(t) = \sum_{i=1}^{N} w_i u_i(t)$$

where $u_i(t)$ is the control action the i^{th} controller would have taken by itself. The error between the desired state and the resulting state is used to adjust the control weighting according to the weight of the responsible controller. Controllers which have a large weights are more responsible for the overall error ~~that ones~~than ones with smaller weights. Therefore, such large

weight controllers should receive correspondingly larger rewards and losses, i.e., correspondingly large increases and decreases in the control weights w_i.

Please replace paragraph **[0044]** with the following rewritten paragraph:

[0044] ~~Fig. 3~~Fig. 2 shows one exemplary embodiment of a system 200 according to this invention. In particular, the system 200 is used to control an air conditioning system 300, for a large residential building or commercial building 1000. Distributed control of the air conditioning system 300 is handled by four distributed control agents 210, 220, 230 and 240 of the control system 200. Each distributed control agent 210-240 manages the smart matter air conditioning controls of a particular air conditioning zone ~~320-340~~310-340, respectively. ~~Fig. 2~~ Fig. 3 shows that each air conditioning zone 310-340 has (1) a condenser 311, 321, 331 and 341, respectively; (2) an air handling unit 312, 322, 332 and 342, respectively; (3) a filtration unit 313, 323, 333 and 343, respectively; (4) a humidification unit 314, 324, 334 and 344, respectively; (5) flow control elements 315, 325, 335 and 345, respectively; and (6) various sensors 316, 326, 336 and 346, respectively, including temperature sensors, humidity sensors, and/or air flow sensors.

Please replace paragraph **[0047]** with the following rewritten paragraph:

[0047] In this exemplary embodiment, each zone ~~310-330~~310-340 has one distributive control agent 210, 220, 230 or 240 that controls that zone 310-340. Each agent 210-240 operates using a particular model. As an example, a first model, employed by a first distributive control agent 210, may place a significant amount of emphasis on airflow control and less emphasis on temperature and humidification control. A second model, employed by distributive control agent 220, may place a significant amount of emphasis on ambient temperature and humidification control and less emphasis on airflow control. A third model, employed by distributive control agent 230, is similar to the first model, but the third model may also take into consideration the movement of cold air from upper floors to lower floors. A fourth model,

employed by distributive control agent 240, is similar to the second model but may also take into consideration the rising of warm ambient air from lower floors to higher floors. A fifth Model, also used by the first and second distributive control agents, is similar to the first model but may also take into consideration ambient horizontal air currents from the front to the back of the building 1000 on all four floors due to heat sources located within the building 1000. Additional models may also be used.

Please replace paragraph **[0048]** with the following rewritten paragraph:

[0048] In Fig. 2, the adaptive controller 400, which may be a microprocessor or other distributed control device, is connected through a first interface 410 with the distributed control devices 210-240, and is used to control the distributed control devices ~~210-24~~210-240. Adaptive controller 400 determines which control model or mix of control models to use to run each distributive control agent 210-240. The distributed control devices 210-240 are connected to each other and to the air conditioning zones 310-340 of the building 1000 via a second interface 420. Using the adaptive controller 400, information can be exchanged between various ones of the zones 310-340 and/or various ones of the adaptive control agents 210-240, and between adaptive controller 400 and various ones of the adaptive control agents 210-240. Similarly, various ones of the zones 310-340 can be controlled by various ones of the adaptive control agents 210-240, while various ones of the adaptive control agents 210-240 can be controlled by the adaptive controller 400.

Please replace paragraph **[0050]** with the following rewritten paragraph:

[0050] Following the steps set forth in Fig. 1, the adaptive control apparatus of Fig. 2 and the agents 210-240 can be used to iteratively control the air conditioning system 300 of the building 1000 shown in Fig. 3 using a market based control ~~approach~~approach.

Please replace the Abstract with the attached amended Abstract.